# Development of Prediction System Model for Mechanical Property in Friction Stir Welding Using Support Vector Machine (SVM)

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ABSTRACT

*The cost and efficiency of experiments and tests, are still a major issue in manufacturing. In this work, a machine learning technique i.e. support vector machine (SVM) is applied to develop a system model for prediction the mechanical property in friction stir welding (FSW) of a 6mm thick AA6061 welded joint. Experimental works are performed to measure the welded structure properties, which focus on the tensile strength based on the governing parameters. In the development of the prediction system model the data obtained from the governing parameters and the tensile strength measurement are classified into two different classes, high and low tensile strength, as input for the SVM classifier through training and testing the data from both classes for pattern classification and model development. The result of the testing and evaluation stage of the proposed system model shown the achievement of the prediction accuracy of 100% for each training and testing system on both classes. The study proved the proposed system model is fully accurate. The methodology given in this paper delivers a useful tool to predict the coming tensile strength of friction stir welded structure based on the governing parameters without conducting experiment and test.*

**Keywords:** *Support Vector Machine, Artificial Intelligent, Friction Stir Welding.*

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ISSN 1823- 5514, eISSN 2550-164X

Received for review: 2017-05-16
Accepted for publication: 2017-10-10
Published: 2018-04-15

## Introduction

More than 2 decades since its inception, friction stir welding (FSW) has shown rapid progress with numerous advantages. Compare to conventional welding FSW presenting its nature of not reaching the melting temperature during welding. These all unique capabilities of FSW are mainly created by combination of two process parameters associated by tool motion i.e. rotational speed and travel speed during welding. Concerning to the figure 1 as shown, the tool rotates at a velocity in Revolutions Per-Minute (RPM), which is referred to as Rotational Speed (RS). The translational velocity at which the tool travels along the joining path is called the feed rate or Travel Speed (TS), and will be given in millimeter per minute (mm/min) [9]. The forces act in three directions along the X-axis, Y-axis, and Z-axis will be referred to as the translational (Fx), transverse (Fy), and axial force (Fz) respectively, and will be given in Newton (N).

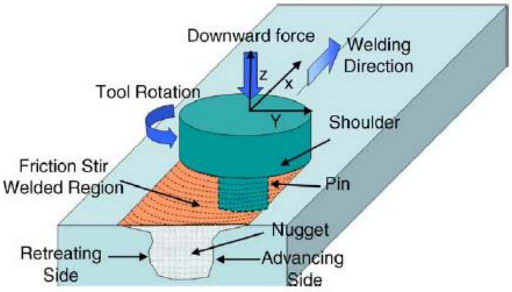


Figure 1: Friction Stir Welding process schematic [1].

A broad of study in the optimization of FSW process has been noted due to its necessity of defining the optimal settings of such process by ascertaining the governed parameters to run properly and smoothly associated to the process to further improvement and performance of the welded structures. However such optimization approaches are competed with cost efficiency of experiments and tests, as the price of raw materials and time consuming. In consequence employing machine learning intelligence systems as an efficient approach to solve engineering problems especially in manufacturing [2-4], and especially in welding [5-6] is considerable. A technique that overtook artificial neural networks in machine learning popularity is support vector machine (SVM) where this is much simpler methods such as linear classifiers gradually [7]. In welding this technique has been recorded in [8-15].

## Support vector machine (SVMs) classification

The idea of SVM is the mapping of non-linearly training data into higher-dimensional feature space through the kernel function used as pattern classification. SVM constructs a hyper-plane in a high dimensional feature space, which can be used for classification, regression or other tasks. Therefore a good separation is achieved by the hyper-plane that has the largest distance to the nearest training data points of any class (functional margin), since in general the larger the margin the lower the generalization error of the classifier (Figure 2). Hence, in the linear separable case, there exists a separating hyperplane whose function is

$$\mathbf{wX} + b = 0 \quad \mathbf{w} \in R^N, b \in R \tag{1}$$

where **w** is weight, and b is bias. For optimized linear division, a hyperplane is constructed to separate the two classes [16]. This implies

$$\mathbf{y_i}(\mathbf{wX} + b = 0) \geq 1, i = 1,\ldots,N \tag{2}$$

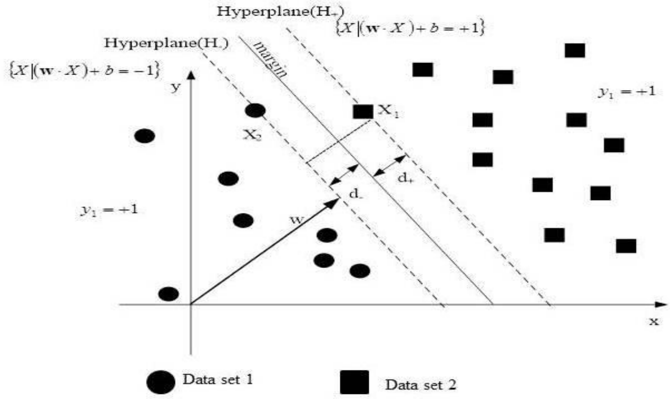


Figure 2: SVM with linear separable data [17].

By introducing Lagrange multiplier $\alpha_i$, the SVM training procedure aims to solve a convex quadratic problem (QP). The solution is a unique globally optimization result, which has the following property:

$$\mathbf{w} = \sum_{i}^{N} \boldsymbol{\alpha}_{\mathbf{i}} \mathbf{y}_{\mathbf{i}} \mathbf{X}_{\mathbf{i}} \tag{3}$$

where $\alpha_i \neq 0$, $X_i$ is called the support vectors. When SVM is trained, a decision can be obtained by comparing each new example $X$ with only the support vector $\{\mathbf{X_i}\}$, $i \in SV$;

$$\mathbf{y} = sign\left(\sum_{i \in SV} \boldsymbol{\alpha}_{\mathbf{i}} \mathbf{y}_{\mathbf{i}} \left(\mathbf{X}_{\mathbf{i}} \bullet \mathbf{x}^{\mathbf{T}}\right) + b\right) \tag{4}$$

where $\mathbf{x^T}$ is the testing data and $SV$ is the support vector data.

## Experimental work

The study concerning mechanical properties of tensile strength in FSW was investigated experimentally. Strength analysis was done on the welded specimens through mechanical tensile test. All the welds were performed in the work-pieces of 6 mm thick plates of AA6061-T651 aluminum alloy perpendicular to the rotating tool in a butt joint arrangement with straight edge preparation as refer to Figure 3.

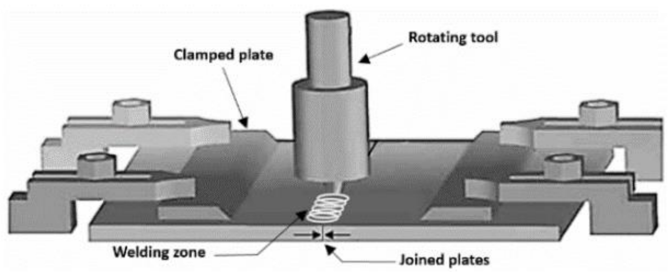


Figure 3: The position of the clamps fixed relative to the surface of the sheet.

Tensile tests were performed under a cross head speed of 5 mm/min according to the EN-895-2002 standard where the tensile specimen dimension are as shown in Figure 4. The room temperature tensile strength of the base and the friction stir processed sheet was evaluated by conducting tensile test on a 250 KN Instron universal testing machine. During uniaxial tensile tests a high resolution extensometer was used. The selected combination of the governing parameter is tabulated in table 1.

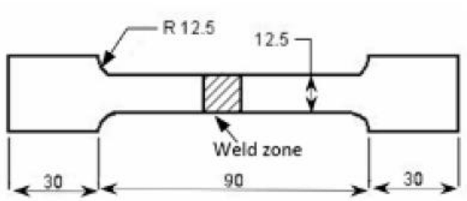


Figure 4: Dimensions of flat tensile specimen.

Table 1: Combination of governing parameter and the tensile test measurement.

| Rotation speed (Rpm) | Traverse speed (mm/s) | Tensile strength (MPa) | | | Mean Tensile strength (MPa) |
|---|---|---|---|---|---|
| | | 1st Speciment | 2nd Speciment | 3rd Speciment | |
| 350 | 0.80 | 149.2 | 149.3 | 148.2 | 148.9 |
| 350 | 1.42 | 169.4 | 169.3 | 171.3 | 170.0 |
| 350 | 2.38 | 167.1 | 169.8 | 170.1 | 169.0 |
| 350 | 3.33 | 187.7 | 189.9 | 188.5 | 188.7 |
| 350 | 4.55 | 190.6 | 191.0 | 185.2 | 188.9 |
| 650 | 0.80 | 142.7 | 150.7 | 152.0 | 148.5 |
| 650 | 1.42 | 174.0 | 175.6 | 175.7 | 175.1 |
| 650 | 2.38 | 194.5 | 192.5 | 192.8 | 193.3 |
| 650 | 3.33 | 189.8 | 188.5 | 188.5 | 188.9 |
| 650 | 4.55 | 196.4 | 196.3 | 198.7 | 197.2 |
| 950 | 0.80 | 135.0 | 144.1 | 143.0 | 140.7 |
| 950 | 1.42 | 166.2 | 167.7 | 161.0 | 165.0 |
| 950 | 2.38 | 172.9 | 191.8 | 182.5 | 182.4 |
| 950 | 3.33 | 187.8 | 181.1 | 178.8 | 182.6 |
| 950 | 4.55 | 204.5 | 209.3 | 207.2 | 207.0 |
| 1400 | 0.80 | 168.2 | 172.6 | 164.5 | 168.4 |
| 1400 | 1.42 | 59.6 | 70.5 | 67.3 | 65.8 |
| 1400 | 2.38 | 110.3 | 108.4 | 100.5 | 106.4 |
| 1400 | 3.33 | 143.6 | 145.4 | 153.7 | 147.6 |
| 1400 | 4.55 | 30.6 | 27.1 | 30.3 | 29.3 |

## Proposed Method for Prediction Model

The objective of this work is to propose a model for prediction the mechanical property of friction stir welded join which focus on the tensile strength based on the governing parameters. The governing parameters will be considered as the input to the proposed prediction system model and then fed into the support vector machine (SVM) classifier in order to produce predicted tensile strength.

SVM method is used as the pattern classification technique that measures the similarities between input data and the data stored in the database. The whole prediction system has two important phases namely, the training phase and testing phase. The training phase is the process of developing the model for the measurement data that will be used as the references for the prediction system. Meanwhile, the testing phase is a process of evaluating the performance of the proposed system. The whole process is described by the flowchart shown in Figure 5. The subsequence sections explain the details of each processing block.

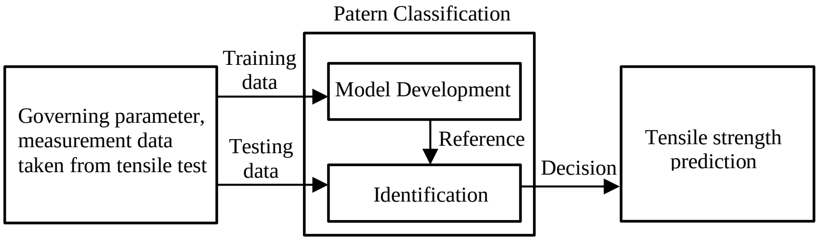


Figure 5: Schematic diagram of proposed algorithm using SVM technique for prediction model.

Table 2: Classification of two tensile strength category.

| Classification | Rotational speed (rpm) | Travel speed (mm/s) | Mean Tensile Strength (MPa) |
|---|---|---|---|
| Low Tensile Strenght | 350 | 0.8 | 148.9 |
| | 350 | 1.42 | 170 |
| | 350 | 2.38 | 169 |
| | 650 | 0.8 | 148.5 |
| | 650 | 1.42 | 175.1 |
| | 950 | 0.8 | 140.7 |
| | 950 | 1.42 | 165 |
| | 1400 | 0.8 | 168.4 |
| | 1400 | 1.42 | 65.8 |
| | 1400 | 2.38 | 106.4 |
| | 1400 | 3.33 | 147.6 |
| | 1400 | 4.55 | 29.3 |
| High Tensile Strenght | 350 | 3.33 | 188.7 |
| | 350 | 4.55 | 188.9 |
| | 650 | 2.38 | 193.3 |
| | 650 | 3.33 | 188.9 |
| | 650 | 4.55 | 197.2 |
| | 950 | 2.38 | 182.4 |
| | 950 | 3.33 | 182.6 |
| | 950 | 4.55 | 207 |

## Model Development and Discussion

The development of the system model is done in this stage. The initial stage of the model development is classifying the data of tensile strength measurement from the tensile test in tandem with combination of related governing parameter. Table 2 shows the measured data that classified into two different classes i.e. high and low tensile strength. The high tensile strength is categorized for the strengths that measured from 180 MPa and higher, where the low tensile strength for the strength that measured from 180 MPa and lower. The classified data are then read and observed by the system model to signify the characteristic of significant change of governing parameters. Based on these characteristic the system model does the next stage where trains the pattern classification. The data that to be used to train the system are stored in the database of the training data (Table 3). The data are then used as the input to the pattern classification stage.

Furthermore testing is required to test the system model through the data from the tensile strength measurement in tandem with combination of related governing parameter, and the reference data from training stage based on the data available in the experiment that are not used to train the system (Table 4). Afterward, the first testing data in Table 4 use the same data as training data, this is due to the limited data of the measurement obtained.

Table 3: A list of data used for training the system.

| Classification | Rotational speed (rpm) | Travel speed (mm/s) | Mean Tensile Strength (MPa) |
|---|---|---|---|
| Training (Low) | 350 | 0.8 | 148.9 |
| | 350 | 1.42 | 170 |
| | 350 | 2.38 | 169 |
| | 650 | 0.8 | 148.5 |
| | 650 | 1.42 | 175.1 |
| | 950 | 0.8 | 140.7 |
| Training (High) | 350 | 3.33 | 188.7 |
| | 350 | 4.55 | 188.9 |
| | 650 | 2.38 | 193.3 |
| | 650 | 3.33 | 188.9 |
| | 650 | 4.55 | 197.2 |

The final stage is completed by testing and evaluating the system model performance of the proposed system model. In Table 5 shows the accuracy of 100% for each training and testing system, either for low tensile strength or high tensile strength classes. This means that the proposed algorithm for system model is fully accurate in predicting the tensile strength for friction stir welded join.

Table 4: A list of data used for testing the system.

| Classification | Rotational speed (rpm) | Travel speed (mm/s) | Mean Tensile Strength (MPa) |
|---|---|---|---|
| Testing (Low) | 950 | 1.42 | 165 |
| | 1400 | 0.8 | 168.4 |
| | 1400 | 1.42 | 65.8 |
| | 1400 | 2.38 | 106.4 |
| | 1400 | 3.33 | 147.6 |
| | 1400 | 4.55 | 29.3 |
| Testing (High) | 950 | 2.38 | 182.4 |
| | 950 | 3.33 | 182.6 |
| | 950 | 4.55 | 207 |

Table 5: Training and testing accuracy of the model.

| No. | Input data category | Training accuracy(%) | Testing accuracy(%) |
|---|---|---|---|
| 1 | Low tensile strength | 100 | 100 |
| 2 | High tensile strength | 100 | 100 |

## Conclusion

The prediction system model for mechanical properties in friction stir welding has been developed in this work. The proposed system model is develop in such away aimed to determine the desire information for the coming tensile strength based on the related governing parameters without reference tensile strength measurement. In the initial stage of the development process the governing parameters and tensile strength measurement are classified into two different class i.e. high tensile strength for 180 MPa and higher, and low tensile strength for 180 MPa and lower. The data on both classes will be then considered as the input to the pattern classification stage. In this stage SVMs classification is implemented for pattern classification and model development for the system model. The data that have been classified are then read and observed by the system model to signify the characteristic of significant change of governing parameters. Based on these characteristic the system model will train and test the pattern classification.

In the final stage the performance of the developed system model is tested and evaluated, where found the prediction accuracy of 100% for each training and testing system, either for low tensile strength or high tensile strength class. This means that the proposed algorithm for system model is fully accurate in predicting the tensile strength for friction stir welded join.

Therefore the proposed system model delivers a useful tool for prediction the tensile strength of friction stir welded structure without applying the tensile test measurement.

## Acknowledgements

Author are thankful to Universiti Teknologi MARA Malaysia and Binus ASO School of Engineering Indonesia for providing the excellent experimental facility on friction stir welding including tensile strength measurement and the development of the system model. Author also thankful to Mohamed Ackiel Mohamed for the dedication in the collaboration of the experiment and test on the mechanical properties of friction stir welded join.

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